A Web Application for Automated Dialect Analysis

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Abstract

Sociolinguists are regularly faced with the task of measuring phonetic features from speech, which involves manually transcribing audio recordings – a major bottleneck to analyzing large collections of data. We harness automatic speech recognition to build an online end-to-end web application where users upload untranscribed speech collections and receive formant measurements of the vowels in their data. We demonstrate this tool by using it to automatically analyze President Barack Obama's vowel pronunciations.

1 Introduction

There has been recent interest in technologies for the automated analysis of web-scale corpora in sociolinguistics, the study of language usage and variation in society. The subfield of sociophonetics is concerned with how certain speech sounds are manifested, giving rise to distinctive speech accents. While there have been computational tools developed for sociophoeticians in the last few years, they require that the speech is manually transcribed at the word level, which is painstaking for large corpora.

Our insight is that, for many types of recordings, transcriptions produced by current automatic speech recognition (ASR) systems are not significantly worse than manual transcriptions for the purpose of measuring certain key phonetic characteristics of speakers, such as their vowel formants – which are essential to dialect research.

We have created an open-access website, DARLA (short for Dartmouth Linguistic Automation)[1], where linguists and other researchers working on speech dialects can upload their data, and receive automatic transcriptions of the recordings as well as measurements of the speakers' vowels. We envision this tool being used by linguists for a first-pass qualitative study of dialect features in speech data without the effort of manual transcription.

We choose to implement the system online rather than as a downloadable toolkit to eliminate the overhead of program installation for users. Furthermore, since this is an ongoing project, it is seamless to incorporate new features in a web application rather than pushing updates to a desktop program. DARLA currently supports English speech.

Details about our methods as well as studies using sociolinguistic data appear in Reddy and Stanford (2015). In this paper, we focus on describing the interface and an overview of the system components.

2 Background

2.1 Vowel Formants

Every vowel sound is associated with a set of resonance frequencies, or formants, characteristic to the vowel as well as the speaker. Sociophoneticians typically study how the first two formants of stressed vowels, denoted by F_1 and F_2, systematically differ across speakers of the language. For example, as shown in Fig. 1, a speaker saying the vowel `EY`[2] (the first vowel in *paper*) with a Southern accent would

[1] http://darla.dartmouth.edu

[2] We use the standard CMU Arpabet phoneme set (http://www.speech.cs.cmu.edu/cgi-bin/cmudict)

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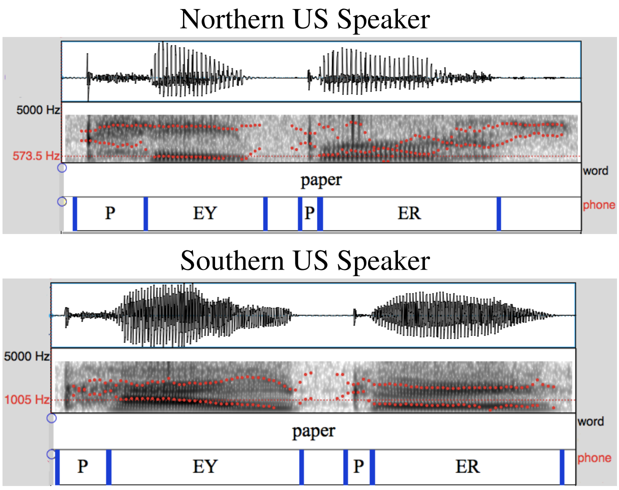
have a higher F_1 and lower F_2 than a Northern US speaker for the same vowel.

Figure 1: Words and phonemes aligned to speech (represented by its waveform and frequency spectrogram, visualized in Praat). The vowel formants are the dark 'bands', or local frequency peaks.



2.2 Motivation

We observe that the stressed vowel error rate of our automatic speech recognition system is about a third of the word error rate for several different test corpora. Unlike typical applications of ASR like dictation or command-and-control systems where accurate word recognition is the primary objective, perfect transcription accuracy is not always necessary. For many sociophonetic purposes, it is sufficient to get the vowel correct. Errors like *depend* in place of *spend* that retain the identity of the stressed vowel account for many of the word errors. Furthermore, with the opportunity to easily analyze speech containing several examples of each vowel type, a few errors will make little difference to the overall dialect analysis.

3 Existing Work

DARLA is inspired by two online tools used by the phonetics and sociolinguistics communities:

1. FAVE (Rosenfelder et al., 2011), short for Forced Alignment Vowel Extraction, takes as input a speech file along with word-level manual transcriptions. It performs Viterbi alignment of the phonemes in the transcription to the speech using HMM-based acoustic models. The locations of vowels are identified from the alignment, and the vowel formants measured at the appropriate locations using Linear Predictive Coding, which in turn is computed by the Praat toolkit for phonetics (Boersma and Weenink, 2014).

Other programs for phoneme alignment include the ProsodyLab Aligner (Gorman et al., 2011) and WebMAUS (Kisler et al., 2012). Recently, Winkelmann and Raess (2014) developed a web tool for spectral analysis and visualization of speech.

The key difference between our system and prior work is that we do not require any transcriptions for the input speech.

2. The NORM suite for vowel normalization and plotting (Thomas and Kendall, 2007) lets users upload formant measurements, and generates scatterplots of the first two formants.

4 System Description

4.1 Input

Fig. 2 is a screenshot of the interface, which is implemented in HTML and Javascript, and connected to the server through CGI and Ajax. Users upload their speech data and can optionally select parameters for the ASR decoder. The options consist of a dialect-specific acoustic model, and the type of speech: free speech or dictation, for which we use a high language model scaling factor, or lists of words – commonly used in sociophonetic research – for which a lower scaling factor is appropriate. Once the upload is complete, users are prompted to enter a speaker ID and sex for each file (Fig. 3), used as parameters for formant extraction. The inputs are validated and sanitized on the client and server sides.

4.2 Back-End Computation

The system currently contains an HMM-based speech recognizer built using the CMU Sphinx toolkit[3], with acoustic and language models that we trained on a variety of American English speech corpora (broadcast news and telephone conversations). We currently have one dialect-specific acoustic model for Southern speech, trained on portions of the Switchboard corpus (Godfrey and Holliman,

[3]http://cmusphinx.sourceforge.net

Figure 2: Input interface for the completely automated vowel extraction system.

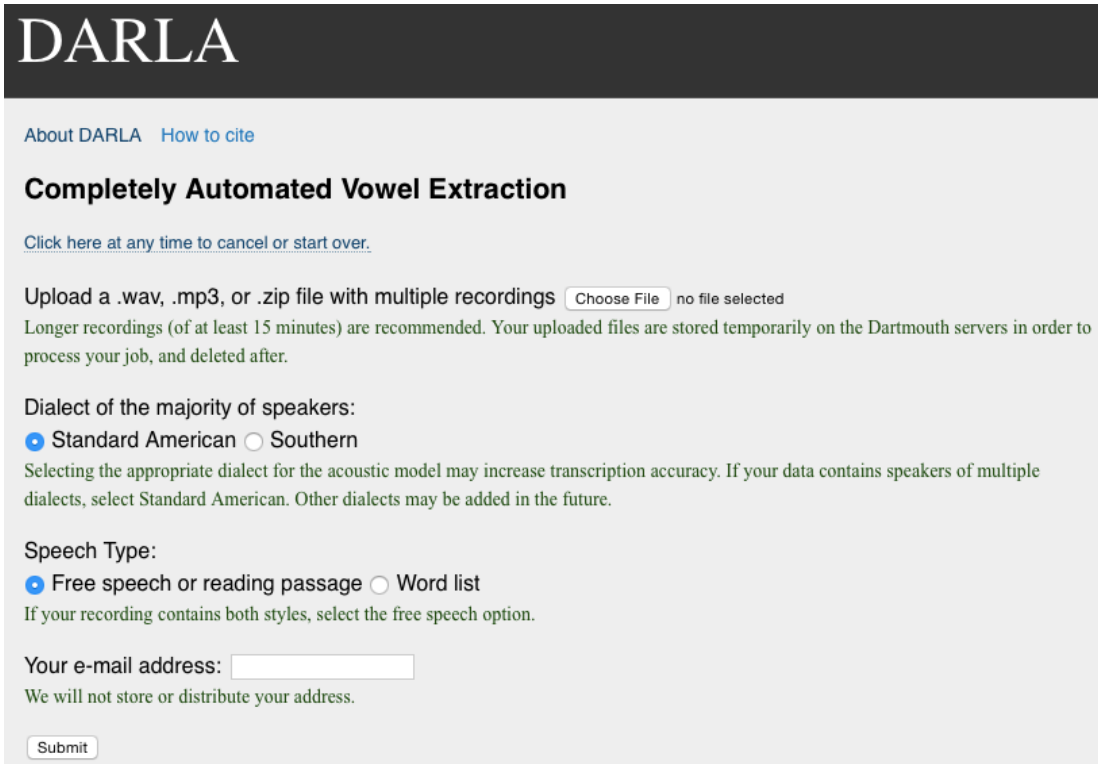
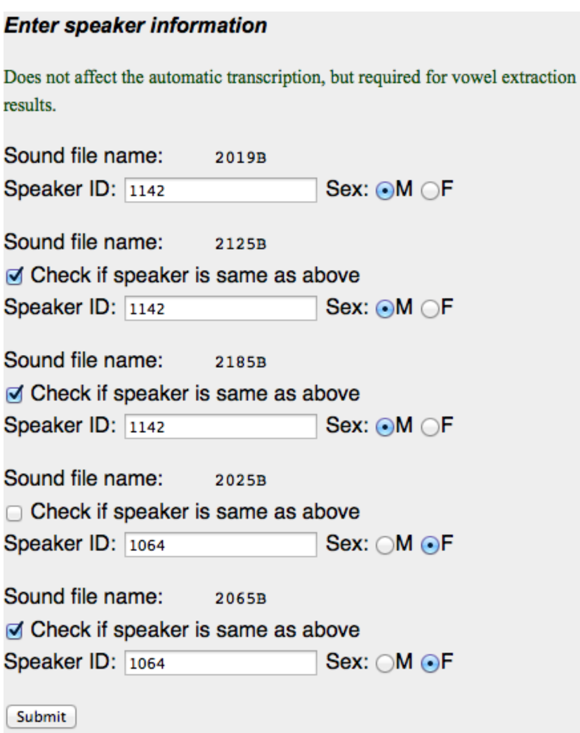


Figure 3: Speaker information prompt.



1993). The feature representation uses 13 MFCCs, deltas, and delta-deltas sampled every 10ms.

Long audio files are split into smaller segments, and down-sampled to 16 kHz (or 8 kHz if the original sampling rate is below 16 kHz). We use PocketSphinx for decoding, and HTK to force-align the output transcriptions to produce phoneme-to-audio alignments. The system then converts the alignments to TextGrid format[4], and uses the formant extraction portion of the FAVE code[5] to measure the formant values for all the vowel tokens in the transcriptions. The processing is distributed over eight CPUs so simultaneous jobs can be supported.

Since the transcriptions are likely to contain errors, we filter out low-confidence vowel tokens based on the acoustic likelihood of the word containing that token under the acoustic model. Previous work on identifying potential errors in the transcription suggests using models of duration in addition to acoustic features (Das et al., 2010), which we plan

[4]Conversion was facilitated by the Python TextGrid library available at http://github.com/kylebgorman/textgrid.py

[5]https://github.com/JoFrhwld/FAVE

to incorporate. We also filter out function words, unstressed vowel tokens, and tokens with high formant bandwidths (indicating that the formant values may not be reliable). Finally, we generate scatter plots of the mean values of the first two formants for each vowel type using the R vowels package[6].

4.3 Output

The results are e-mailed to the user once the task is completed. The e-mail includes scatter plots of the first two vowel formants for each speaker, and the complete raw formant data in a CSV file which is adapted from the output of FAVE. This file contains the raw formant measurements of every vowel, including the unfiltered tokens, the formant bandwidths, the phonetic contexts, adjacent words, and other relevant information.

Phonetic contexts are particularly important since many vowel shift patterns are context-dependent. We separate the phonetic contexts into place, manner, and voicing features – for example, the sound `P` would be represented as {place: bilabial, manner: stop, and voicing: unvoiced}. Probabilities are computed under the acoustic model for each of these features. This allows researchers to discard low-probability contexts, or incorporate the probabilities as a gradient measure of the phonetic environment.

The e-mail also includes the filtered formant measurements formatted in a tab-separated file for input to the NORM plotting suite in case the user wants more plotting options, and the aligned ASR transcriptions as TextGrid files, which can be opened by Praat and visualized as in Fig. 1. The user can then check the transcriptions and alignments, make corrections as needed, and re-run the formant extraction step using FAVE for more accurate vowel measurements if desired.

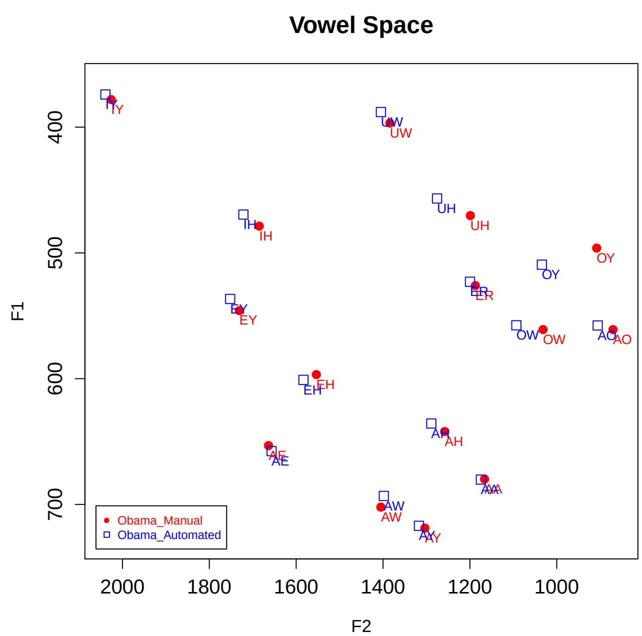
5 Case Study: Obama's State of the Union

We ran the audio of US President Barack Obama's 2015 State of the Union address[7] through our system. The audio of the address is reasonably clean, but the speech is sometimes interrupted by clapping sounds and background noise. The recording is a just over an hour long, and contains 6793 words according to the manual transcript. The decoding, alignment, and formant extraction pipeline takes about 90 minutes to complete.

The ASR transcriptions show a 42% word error rate, and a total stressed vowel error rate of 13%. Of the filtered tokens, the stressed vowel error rate is even better at 9%.

The mean formants from the ASR transcriptions are similar to the formants extracted from the manual text (Fig. 4). The largest discrepancies are in vowels like `OY` which occur less frequently.

Figure 4: Plot of formants averaged over filtered tokens of stressed vowels. This plot shows Obama's vowels as exhibited in the 2015 State of the Union, analyzed using ASR as well as manual transcriptions for comparison. This is the scatterplot that the user receives in the e-mailed output (except that the manual transcription results will not be included).



Obama's regional background is often described as a mix of Hawai'i where he spent most of his childhood, Kansas (his mother's home), and Chicago where he worked for much of his professional life. Sociolinguists have shown that children usually acquire most of their dialect features from peers in the local community, not their parents (Labov, 1991). We therefore expect to find influences from Hawai'i

[6] http://cran.r-project.org/web/packages/vowels

[7] The speech and transcripts are taken from http://www.americanrhetoric.com/barackobamaspeeches.htm

and Chicago, and perhaps also a politician's tendency to appeal to a wider audience: in this case, a general northern US audience.

The results in Fig. 4 indicate that Obama has a mix of conservative Northern US vowels with some Midland and Southern influences, based on sociolinguistic dialect descriptions (Labov et al., 2006; Labov, 2007; Eckert, 2008).

(1) In this data, Obama does not show an advanced stage of the Northern Cities Vowel Chain Shift (NCS) prevalent in Chicago. The F_1 of Obama's `AE` vowel is lower than average, which is a prevalent pattern in Chicago, but also in other regions of the US.

(2) He shows clear evidence of "fronting" (high F_2) of the vowels `UW` (*boot*) and `UH` (*hood*). This pattern is common in the West and other regions, and is spreading to the North.

(3) His `AO` and `AA` vowels are distinct, which is common for Chicago and the Inland North and the South, but interestingly, not the West and Hawai'i.

(4) Finally, his `AW` (*bout*) is somewhat fronted – a feature of the Midland and South.

We also analyzed Obama's previous State of the Union addresses and found that his vowels have remained remarkably stable since 2011.

6 Future Work

Since our system is an ongoing project, we will be rolling out several new features in the upcoming months. We are developing an interface to allow users to make corrections to the speech recognition transcriptions (with low-confidence regions highlighted), and receive updated formant measurements. In the longer term, we hope to expand beyond vowel formants by developing phonetic feature classifiers for other dialect variables such as rhoticity, nasality, and prosody. Finally, since the speech recognizer is the most vital component of the system, we are working on improving the ASR error rate by incorporating state-of-the-art technologies that use deep neural nets.

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